

Problems of Sensor Placement for Intelligent Environments of Robotic Testbeds

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Abstract

In this paper, we consider problems of sensor placement for intelligent environments of robotic testbeds. In particular, we consider the problem of sensor placement and the problem of sensor placement for triangulation based localization. We present experimental results for these problems. Also, we use artificial physics optimization algorithms for solution of the problem of sensor placement. We consider artificial physics optimization for different virtual forces. In particular, we use Runge Kutta neural networks for the calculation of values of virtual forces.

Mathematics Subject Classification: 65-05, 68T40, 65L06

Keywords: sensor placement, satisfiability, artificial physics optimization, virtual force, Runge Kutta neural network

1 Introduction

Intelligent environments are utilize various sensor networks for many different purposes. In particular, we can mention security-oriented sensor placement

in intelligent buildings (see e.g. [1]), condition-based placement of distributed active vision sensors for guiding robots in intelligent environment (see e.g. [2], and optimal sensor placement for hot server detection in data centers (see e.g. [3]). In this paper, we consider algorithms for sensor placement in intelligent environments of robotic testbeds.

There are a number of different problems of sensor placement for intelligent environments of robotic testbeds. In particular, it should be mentioned coverage problems for wireless sensor networks, coverage problems for visual surveillance systems, coverage problems for distributed energy supply systems, different problems of placement visual landmarks, etc.

Note that coverage and placement problems for sensors extensively studied (see e.g. [4] – [10]). In particular, there are a number of different algorithms for sensor placement problems (see e.g. [11]). It should be noted that different sensor placement problems received a lot of attention recently (see e.g. [12] – [18]). In particular, it were obtained explicit polynomial reductions from the problem of sensor placement SP to MAXSAT, SAT and 3SAT (see [14, 15]). Explicit polynomial reductions from the decision version of the problem of sensor placement for triangulation based localization SPP to SAT and 3SAT were proposed in [18]. It is easy to see that we can use SP and SPP to solve problems of sensor placement for intelligent environments of robotic testbeds.

Note that explicit reductions allow us to obtain exact solutions for sensor placement problems. It is clear that we can use exact solutions as training sets for different intelligent algorithms. In this paper, we consider artificial physics optimization algorithms (see e.g. [19] – [21]) for solution of SP and SPP.

2 SAT Solvers for SP and SPP

In this section, we consider SAT solvers for explicit polynomial reductions from SP to MAXSAT and 3SAT (see [14, 15]) and for the explicit polynomial reduction from SPP to 3SAT (see [18]). Note that some SAT solvers for SP and SPP were considered in [16, 18]. In this section, we consider

- A1** genetic algorithm with expansion and exploration operators for MAXSAT (see [22]);
- A2** GSAT with adaptive score function (see [23]);
- A3** genetic algorithm with exons and introns (see [24]);
- A4** genetic algorithm with expansion operator (see [25]).

Let \mathbf{Z} be some set of integers. Let $R \subseteq \mathbf{Z}^2$ be a discretized workspace for SP. Following [14], we assume that $N \subseteq R$ is a set of target locations. Respectively, $S \subseteq R$ is a set of candidate sensor locations.

We use heterogeneous cluster (500 calculation nodes, Intel Core i7). We use the generator of natural instances for SP (see [16]). We consider instances with N and S from 400 to 600 (see [16]). Selected experimental results for SP are given in Tables 1, 2.

time	average	max	best
fgrasp (see [26])	38.1 min	11.27 h	2.12 min
posit (see [26])	42.32 min	8.26 h	2.97 min
SGA (see [16])	1.14 h	21.84 h	2.17 min
OA (see [16])	17.77 min	8.18 h	19 sec
A2	19.44 min	6.38 h	11.2 sec
A3	4.07 min	41.62 min	1.1 min
A4	6.15 min	4.2 h	6 sec

Table 1: Experimental results for explicit polynomial reduction from SP to 3SAT

time	A1	SGA (see [16])	OA (see [16])
average	6.19 min	52.1 min	32.16 min
max	12.74 min	21.3 h	17.6 h
best	1.5 min	53 sec	11 sec

Table 2: Experimental results for explicit polynomial reduction from SP to MAXSAT

Now we consider SAT solvers for SPP. We assume that W is a set of target locations. Respectively, Q is a set of candidate sensor locations. Let $W = \{1, 2, \dots, m\}$ and $Q = \{1, 2, \dots, n\}$. Selected experimental results for SPP are given in Tables 3 – 5.

time	average	max	best
fgrasp (see [26])	23.4 min	1.37 h	3.19 min
posit (see [26])	29.82 min	2.09 h	2.41 min
GA (see [18])	45.36 min	3.62 h	28 sec
A2	12.17 min	52.44 min	8.5 sec
A3	2.26 min	21.7 min	37.3 sec
A4	3.59 min	1.18 h	5.32 sec

Table 3: Experimental results for explicit polynomial reduction from SPP to 3SAT where $n = m = 300$

time	average	max	best
fgrasp (see [26])	42.3 min	2.92 h	8.92 min
posit (see [26])	58.4 min	4.7 h	9.14 min
GA (see [18])	1.03 h	5.13 h	33.4 sec
A2	26.8 min	1.22 h	9.16 sec
A3	3.19 min	24.9 min	44.1 sec
A4	9.11 min	1.53 h	6.22 sec

Table 4: Experimental results for explicit polynomial reduction from SPP to 3SAT where $n = m = 350$

time	average	max	best
fgrasp (see [26])	2.56 h	7.11 h	22.3 min
posit (see [26])	2.43 h	9.48 h	28.7 min
GA (see [18])	2.19 h	6.2 h	53.55 sec
A2	39.72 min	3.79 h	15.88 sec
A3	5.7 min	26.1 min	45.9 sec
A4	14.55 min	1.78 h	7.41 sec

Table 5: Experimental results for explicit polynomial reduction from SPP to 3SAT where $n = m = 600$

3 An Artificial Physics Optimization for the Problem of Sensor Placement

In this section, we consider an artificial physics optimization algorithm for SP. In particular, we consider artificial physics optimization for different virtual forces. Also, we use Runge Kutta neural networks (see e.g. [27]) for the calculation of values of virtual forces.

Note that various nature-inspired heuristics have proven very effective for solving different global optimization problems (see e.g. [19]). In particular, the artificial physics optimization is motivated by the success of “Artificial Physics” as a metaphor for controlling multi-robot systems (see [28, 29]). Artificial physics optimization algorithms use three procedures: initialization, calculation force and motion (see [19]). In an artificial physics optimization algorithm, a swarm of individuals is sampled randomly from a problem space in the initialization. Masses of individuals of the swarm should be calculated in the procedure of calculation force. The procedure of motion uses the total force to calculate the velocity of individuals. Note that a felicitous design of force law can drive individuals search problem space intelligently and efficiently. Therefore, the main advantage of artificial physics optimization algorithms consists

in the proper design of force law.

Different virtual forces are considered (see e.g. [19]). In particular, we can mention negative exponential force law (NEFL), unimodal force law (UFL), linear force law (LFL) [19]. It is well-known that Runge Kutta neural networks can be used for the prediction of different nonlinear systems [27]. Therefore, we use Runge Kutta neural networks for the design of a general force law (RKFL).

We consider 4-order Runge Kutta neural networks with multilayer perceptron networks. We use a gradient learning algorithm for 4-order Runge Kutta neural networks.

Let T_{opt} be the number of sensors for an optimal solution of SP. Let T_A be the number of sensors for a solution of SP with the algorithm A . Let

$$M_A = \frac{T_A}{T_{opt}}.$$

We can consider M_A as a measure of the quality of the algorithm A . Selected experimental results are given in the Table 6.

	$5 \cdot 10^2 \leq N \leq 10^3$ $10^2 \leq S \leq 5 \cdot 10^2$	$5 \cdot 10^3 \leq N \leq 10^4$ $10^3 \leq S \leq 5 \cdot 10^3$	$5 \cdot 10^4 \leq N \leq 10^5$ $10^4 \leq S \leq 5 \cdot 10^4$
M_{NEFL}	1.542	1.789	2.116
M_{UFL}	1.873	2.442	3.715
M_{LFL}	2.292	3.788	5.204
M_{RKFL}	1.076	1.138	1.157

Table 6: An average number of sensors for different algorithms.

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